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Oil production monitoring and optimization from produced water analytics; a case study from the Halfdan chalk oil field, Danish North Sea

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Abstract: Produced water analysis is a direct source of information to the subsurface processes active in an oil field. The information is, however, complex and requires a multidisciplinary approach and access to multiple data types and sources to successfully unlock and decode the processes. We apply data analytics on a combined data set of water chemistry and oil and gas production data measured in the production stream from five wells in the Halfdan field. The field is produced applying extensive water injection to ensure the most efficient water sweep of the reservoir. Relationships between daily production data and water chemistry are examined with Principal Component Analysis (PCA), and systematics with respect to predictability of daily changes in the oil production from water chemistry are examined with partial least square (PLS) regression models. For each well, the water chemistry provides a high degree of predictability with respect to daily oil cut in the production stream. The results have potential for application within prediction of sweep efficiency, by-passed oil and for prediction of water break-through. Full potential, however, depend on successful implementation of water chemistry-oil production analytics into other data domains such as seismic (4D) data and well work-over data.

Keywords: Big Data, History Matching, Reservoir Simulation Optimization and Management, Production Monitoring, Automation and Optimization.

1. INTRODUCTION

Today reservoir monitoring is challenged by its expense and technical difficulty. Incorporation of new and relevant data sets are cumbersome implying infrequent updating of the knowledge base. By improving the reservoir management there will be opportunities to accelerate or increase production and improve operational efficiency. If one can link data from the reservoir, wells, and facilities monitoring and sensing devices to the subsurface model the obtained information can be valuable for making business decisions. The aim is to create *smart oil fields* by developing automated systems in a cross-disciplinary collaboration between geoscientists, engineers, and other domain specialists. One opportunity is to obtain real-time history matching in order to monitor changes in key physical reservoir parameters and from that implement the necessary changes to optimize field performance. For instance, the design process must establish how to handle ever-increasing levels of water production.

A key ingredient in establishing real-time reservoir management is to increase the efficiency of data utilisation and sharing, and this includes understanding the chemical reactions and phase changes associated with reservoir multiphase flow conditions.

Oil and gas production in the Danish North Sea began in 1972 and is projected to be substantial in terms of domestics needs until 2035 (Danish Energy Agency 2017). Production occur from highly porous but low permeable chalk reservoirs in which water flooding of the reservoirs has proven to be the key to enhance oil recovery.

In 2015, the oil production from Danish fields was 9.1×10^6 m^3, however this volume was dwarfed compared to the volumes of water handled on the installations either as co-produced water or as injected water (Fig. 1). As the fields have matured, the volume of water to be handled has increased dramatically with a consequently high demand of energy needed for handling these large volumes, which may exceed 90% for some fields.

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Apart from being a waste product the produced water carries important information on reservoir dynamics and recovery processes (Schovsbo et al. 2016, 2017). The produced water can originate from natural water zones in the reservoir or from the water injection water, and its origin and relationship to oil and gas recovery is important for any field development, production monitoring and history matching.

We here present a case study from the Halfdan field in the Danish part of the North Sea (Fig. 2) with the aim to establish the first principles governing oil production monitoring and optimization from produced water analytics.

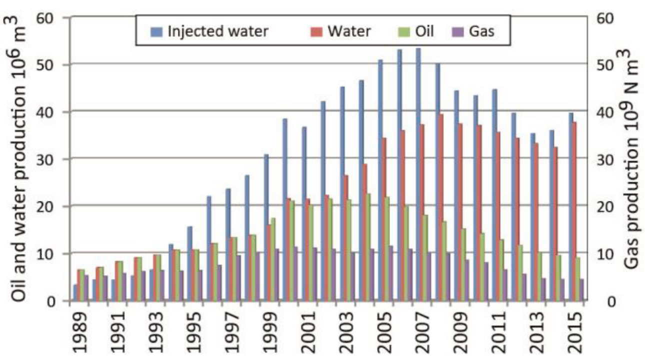

Fig. 1. Production and water injection volumes from Danish fields in the North Sea in the period 1989-2015. Data source: Danish Energy Agency.

2. GEOLOGICAL SETTING

2.1 Chalk reservoirs and water flooding

The reservoir rock formed during the Cretaceous-Lower Palaeogene period (62-145 million years ago) and is composed of chalk consisting of the remains of calcareous microorganism shells (Hjuler and Fabricius 2009). Chalk is very porous (25-45%) but has low permeabilities (0.5-2 mDarcy) and thus production has been challenging.

Initially, the chalk fields were produced from vertical wells by compaction drive in which the fluid expansion caused by pressure relief was the main driver for production. However, since 1986 water injection was initiated (Fig. 1) to give pressure support and to sweep oil from injector well to the producer thereby greatly enhancing oil recovery.

2.1 The Halfdan field

The Halfdan field (Fig. 2) was discovered in 1998 and had first oil produced in 1999. The field is developed in an alternating pattern of km-long multistage horizontal producer and water injector wells aimed at maximum water sweep efficiency by applying the Fracture Aligned Sweep Technology (FAST) concept, developed by Mærsk Oil (Lafond et al. 2010). Several first moves with respect to technology implementation have been made for the field with respect to optimisation (Calvert et al. 2014, 2016; Wherity et al. 2014). The key for success in these studies has been to link well data representing performance over many km and stimulation zones with seismic data revealing the spatial geometry.

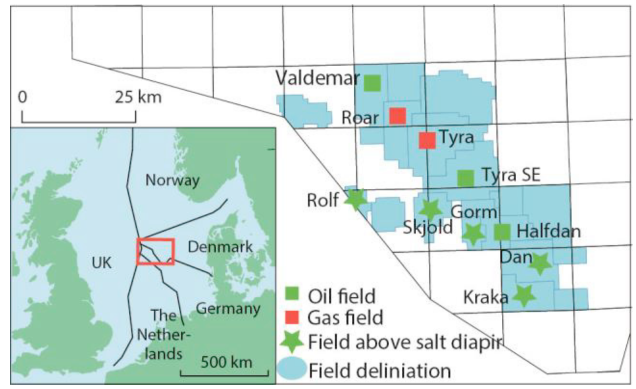

Fig. 2. Southern part of the Danish North Sea showing the ten producing fields included in this study.

3. DATA AND METHODS

3.1 Regional produced water chemical analysis

For a regional characterisation of the produced water types, 314 water sample analyses were included from ten producing chalk fields in the southern part of the Danish North Sea (Fig. 2). The samples represent a selection of all available chemical measurements from the fields aimed to give a representative overview of the types of water produced from the fields. For characterisation, samples analysed for Na^+, K^+, Ca^{2+}, Mg^{2+}, Sr^{2+}, Ba^{2+}, Cl^-, and SO_4^{2-} were used. No information on methods or sampling protocols for the specific samples was available.

3.2 Production data from the Halfdan field

Production data from five wells (named well A to E) from the Halfdan field was selected to represent different scenarios with respect to temporal and spatial variation in water chemistry and oil production. Well A, B and C are positioned central in the field and well A and B share the same water injector well. The periods studied are up to 1st of January 2013 and include the first 9.2 to 11.4 years of production.

Production data include average daily oil, gas and water production and 390 analysed samples of produced water with a somewhat irregularly sample frequency. Calculated variables include: Production days calculated as numbers of days from first production, gas to oil ratio (GOR) calculated as the gas to oil volume ratio x 1000 and the oil fraction in the production stream calculated as oil production rate divided by the total fluid rate (sum of oil and water production rates). The production data was combined with water chemical analysis so that data sets obtained on the same day were combined with each other.

3.3 Principal Component Analysis (PCA)

PCA transforms a matrix of measured data (N samples, P variables), X, into sets of projection sub-spaces delineated by Principal Components (each a linear combination of all P variables), which display variance maximised interrelationships between samples and variables, respectively (Martens and Næs 1989; Höskuldsson 1996; Esbensen 2012, Esbensen et al. 2015). PCA score plots display groupings, or clusters, between samples based on compositional similarities, as described by the variable correlations (shown with accompanying loading plots), and also quantify the proportion (%) of total data-set variance that can be modelled by each component. All data analyses in this work are based on auto-scaled data [X-X(avr)/std].

3.4 Partial Least Squares (PLS) regression

PLS regression replaces the classical multiple linear regression and allows direct correlations to be modelled between y and the multivariate X data, compensating for debilitating co-linearity between x-variables, (Martens and Næs 1989; Höskuldsson 1996; Esbensen 2012). PLS regression models are used extensively in science, technology and industry for prediction purposes where the critical success factor is proper validation (Esbensen and Geladi 2010). Both PCA and PLS result in informative score plots, loading plots (PLS: loading-weights) and prediction validation plots, which are the prime vehicles for detailed interpretation of complex data relationships. PLS components are based on [X,y] covariance optimisation, but the scientific interpretation of the derived scores and loading-weights plots follows procedures which are identical to the PCA (c.f. Esbensen et al. 2015). Validation was based on a test set prepared before modelling: The data for each well was sorted with respect to production day before being randomly split into two independent data sets, i.e. the training versus the test set, securing a realistic prediction performance validation (Esbensen 2012; Esbensen and Geladi 2010).

Modelling (PCA and PLS) was performed in the software package Unscramble® 10.5 from CAMO.

4. RESULTS

4.1 Regional water types in Danish fields

In the PCA model of the regional water chemistry database, the first two PCA axes resolve 77% of the total data variance (Fig 3). The three main clusters of variables in the PCA-1 versus PCA-2 diagram are Ba^{2+} characterized by high positive PCA-1 loadings, a clustering of SO_4^{2-}, Mg^{2+} and K^+ characterized by high negative PCA-1 and PCA-2 loadings and a clustering of Cl^-, Na^+, Sr^{2+} characterized by high negative PCA-1 and positive PCA-2 loadings (Fig. 3B).

The clustering of variable reflects different signatures of formation water as exemplified from calculation of average compositions of samples selected within the PCA-1 versus PCA-2 sample score plot (Fig. 3A). Formation Water 1 (FW1) is characterised by high Ba^{2+} concentrations and low overall ionic strength (Table 1). This water type is present in the Valdemar, Roar and Tyra fields (see Fig. 2 for location). Formation Water 4 (FW4) and is characterised by high salinity, medium SO_4^{2-} concentration and no Ba^{2+}. This water type is most clearly expressed in fields above salt domes such as the Kraka field (Fig. 3). An additional water type (SW) is characterised by high SO_4^{2+}, K^+ and Mg^{2+} concentrations (Table 1). This water type is present in the Dan, Halfdan, Gorm and Skjold fields and is interpreted to be the result of decades of extensive water flooding performed by the operator (cf. Schovsbo et al. 2016).

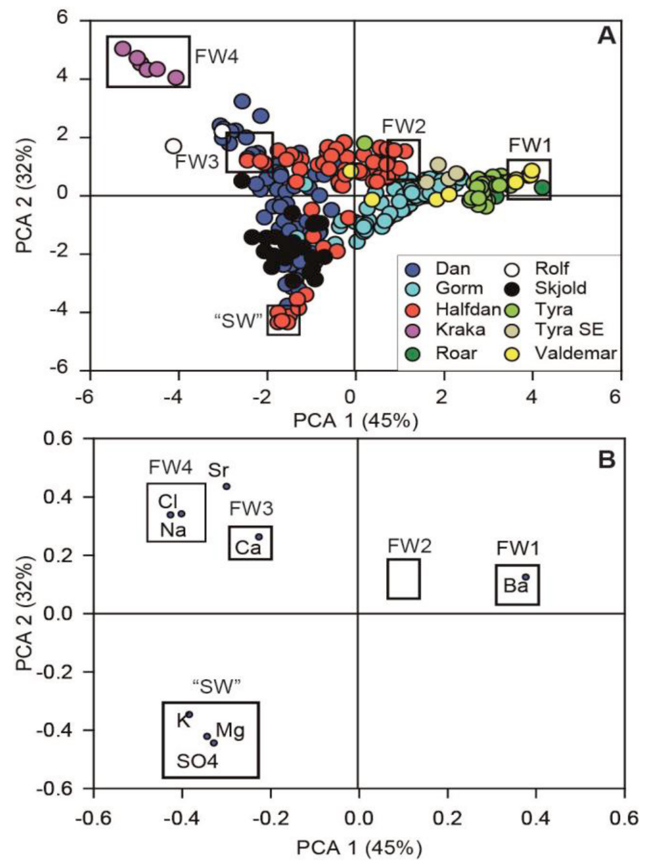

Fig. 3. PCA-model [water chemistry]. A: Score and B: Loading relations for 314 selected samples in ten chalk fields. The plot models 77% of the total data variance. Boxes, FW (Formation Water) 1-4 and SW (Sea Water) denotes identified groupings.

Table 1. Average chemical composition of water types

Element mg/l	SW	FW1	FW2	FW3	FW4
Na^+	11923	10399	17006	24732	41095
K^+	392	84	120	189	216
Mg^{2+}	1225	108	217	369	495
Ca^{2+}	505	363	918	3282	2533
Sr^{2+}	15	61	94	195	371
Ba^{2+}	0	49	8	1	0
Cl^-	20793	16239	27882	42208	68449
SO_4^{2-}	2528	13	69	487	538

FW: Formation Water. SW: Produced water like injected seawater. SW, FW2, FW3, FW4 are from Schovsbo et al. (2017).

In the case of the Halfdan field the formation water composition ranges between the end-members FW1 and FW4 (Fig. 3A). Average compositions of these local end-members (c.f. Schovsbo et al. 2017) are presented in Table 1 and include a Formation Water 2 (FW2) that is characterised by medium to low salinities and medium high Ba^{2+} concentrations and a Formation Water 3 (FW3) that is characterised by high Ca^{2+} and medium high salinities and medium to low SO_4^{2-} concentrations (Fig. 3A). This type is also present in the Dan field.

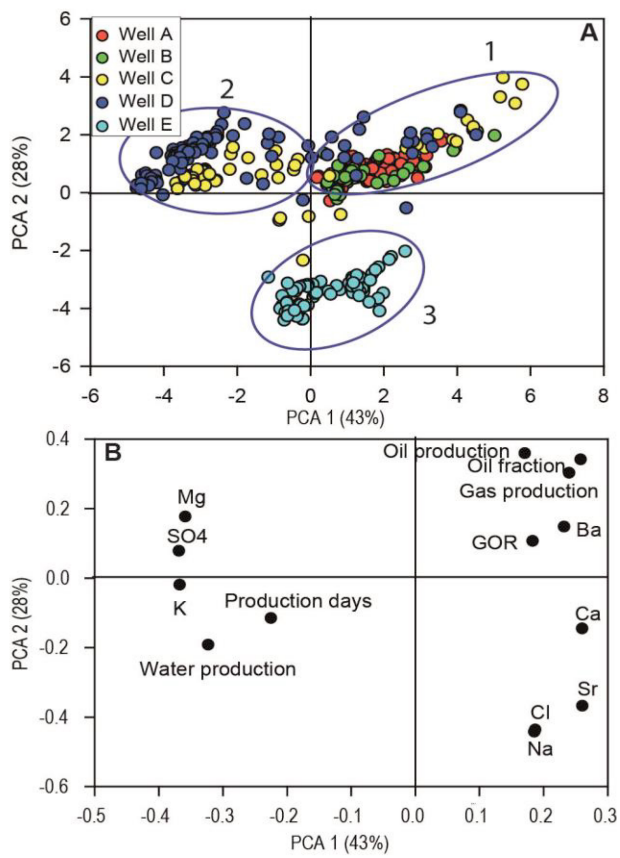

Fig. 4. PCA-model [water chemistry and well production] from five Halfdan wells (A-F). A: Score and B: Loading relations for the full training data set. Proportions of total data variance modelled shown along each PCA-component (%). Circles outline three main sample groupings (1-3) discussed in the text.

4.2 Relationship between production and water chemistry on the Halfdan field

In the PCA model of the combined production related data and water chemistry data set for five Halfdan wells the first two PCA axes resolve 71% of the total data variance (Fig 4). In the loading plot (Fig. 4B) oil and gas production, oil fraction and GOR cluster together with Ba^{2+} at positive PCA-1 and PCA-2 loading values. Water production cluster with production days, SO_4^{2-}, K^+ and Mg^{2+} at negative PCA-1 and intermediate positive and negative PCA-2 loadings. Cl^-, Na^+, Ba^{2+} and Sr^{2+} cluster together and plot with high positive PCA-1 and negative PCA-2 loadings (Fig. 4B).

The clustering of variables are as expected from the general understanding that high oil and gas production is associated with production of formation water, which tends to occur early in the production history of the well. High water production occurs later in the well history and this water resembles seawater reflecting production of injected water (Fig. 4B).

The sample score plot of the two first PCA axes show three main groupings (Fig. 4A). Group 1 consists of well A and B and a few samples from well C and D is characterized by positive PCA-1 and PCA-2 score values. Group 2 consist of the remaining parts of well C and D and is characterized by negative PCA-1 and positive PCA-2 scores. Group 3 include well E and is characterized by high negative PCA-2 scores (Fig. 4A).

The different groupings reflect different relationships between well performance with respect to oil and gas production and chemical composition of the produced water. Group 1 is characterised by high oil and gas production. The water production is low and characterised by high Ba^{2+} and typical of FW2. This zone can also be termed the "sweet spot" in the production. Group 2 and 3 reflect a production mode characterised by low oil fraction and water resembling either SW i.e. injected seawater (SO_4^{2-}, Mg^{2+}, K^+) or a saline formation water, FW3, (Cl^-, Na^+) respectively.

4.3 Prediction of oil fraction in the production stream

The different relationships between well performance and water chemistry can also be illustrated in a PLS-regression model aimed at predicting the oil fraction from the water chemistry and the duration of the production (Fig. 5). Overall the PLS model (Fig. 5) resembles the PCA model presented in Fig. 4. The prediction of the PLS model gave a reasonable satisfactory validation results (slope 0.80; $r^2 = 0.80$ for PLS component 3, Fig. 5). Negative correlation between Cl^- and oil fraction is present in well E and negative correlations between days in production, SO_4^{2-}, Mg^{2+}, K^+ and oil fraction is seen for the remaining wells.

It is noteworthy that samples from well A and B plot closely together in contrast to well C and D that plot along the full range of PLS-1 values with the majority of the samples from Well D plotting with high negative values (Fig. 5A). This well also plot with much lower positive PLS 1 values than well A, B and C suggesting a lower overall performance with respect to high oil fraction than well A, B and C. In these wells the samples with high positive PLS-1 values represent early production in the well characterised by high oil fraction and the group with low negative PLS-1 values represent mid to late production representing low oil fraction. The shift is sudden (few intermediate values) likely reflecting influx of injected seawater via fractures.

For individual groups of wells with similar performance PLS models, using full chemical variables and duration of production, predicts oil fraction with a much more satisfactory validation result than for all wells. This is exemplified with well group A, B and C and well group D and E prediction versus reference plot in Fig. 6D and H. In well group A, B and C (slope 0.88; $r^2 = 0.89$, PLS component 1), oil fraction model is primarily carried by positively correlated Na^+ , Cl^- and Sr^{2+} and negatively correlated SO_4^{2-}, K^+ and Mg^{2+}, but several other composition variables also have minor, but significant influence (Fig. 6B).

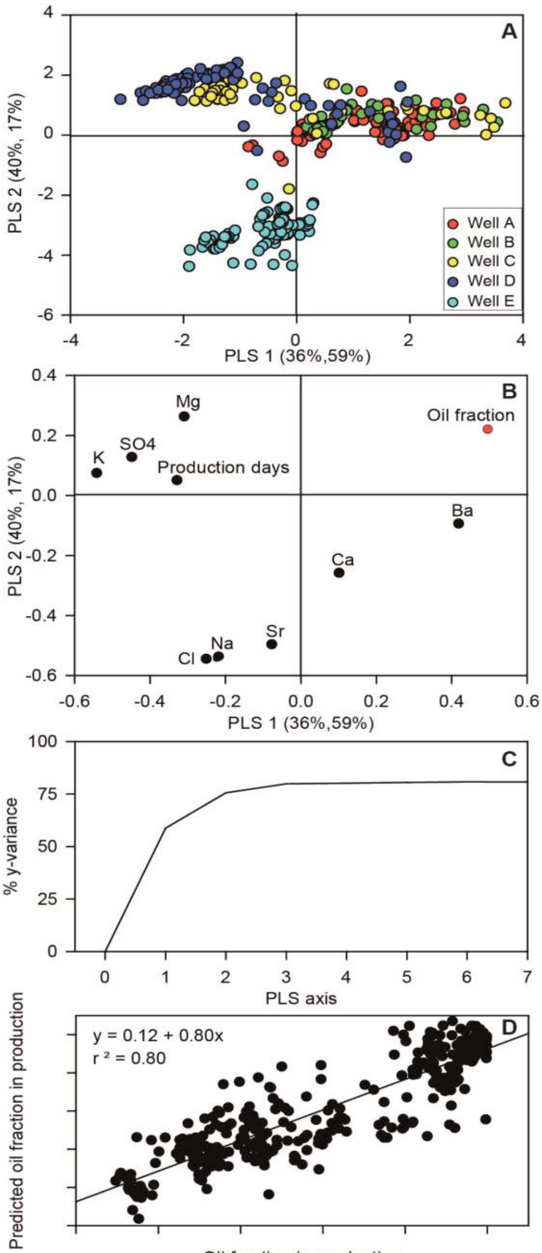

Fig. 5. PLS-regression model for [water chemistry and production day, oil fraction in production] variable set; full training set for five Halfdan wells. A: PLS X-space score plot (t1-t2). B: Corresponding loading-weights plot (w1-w2). C: Modelled y-variance. D: Prediction versus reference plot. Outliers were deleted from the original data set. Proportions of total data variance modelled shown along each PLS-component [X%, y%].

In well group D and E (slope 0.85; $r^2 = 0.86$, PLS component 2), the oil fraction model is primarily carried by positively correlated Ca^{2+} and negatively correlated to production days. Here other composition variables have minor, but yet significant influence with K^+ appearing to have least influence on the correlation (Fig. 6F).

5. DISCUSSION

5.1 Factors influencing the produced water composition

The data presented in this paper stems from chemical analysis of produced waters. The aim of these specific chemical analyses is to determine the accurate concentration of the ions in the water. Some uncertainty lies within the chemical analysis, but the main uncertainty in the data originates from the quality of the samples.

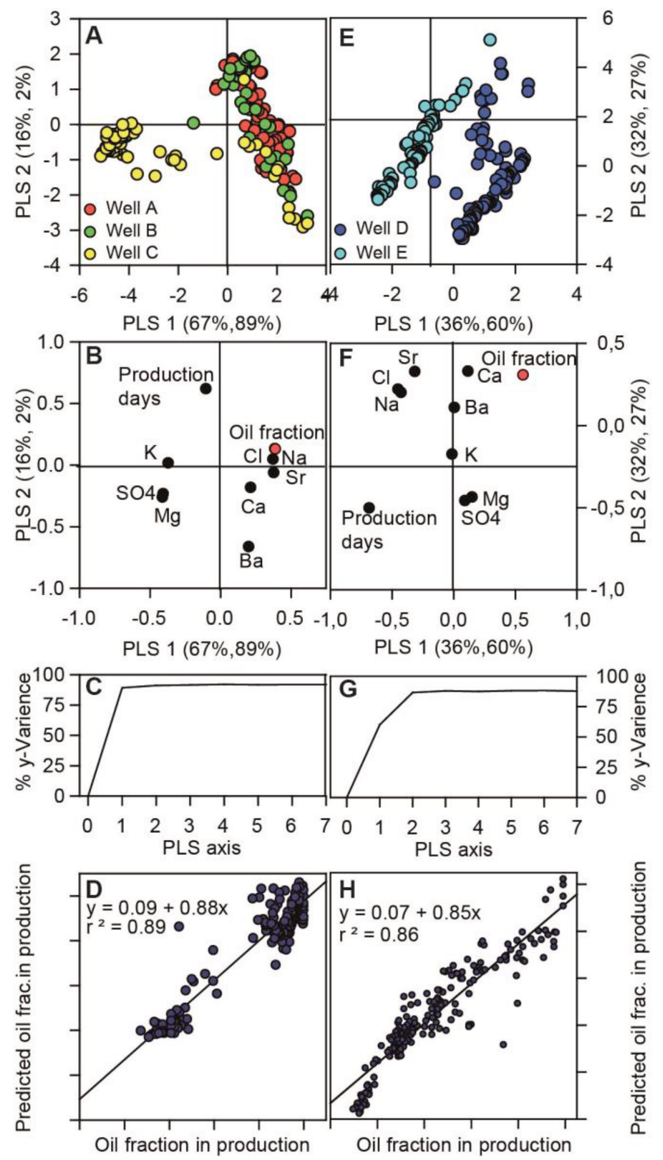

Fig. 6. PLS-regression model for well A, B and C (A-D) and well D and E (E-H) [water chemistry and production day, oil fraction in production] variable set; full training set. A and E: PLS X-space score plot (t1-t2). B and F: Corresponding loading-weights plot (w1-w2). C and G: Modelled y-variance. D and H: Prediction versus reference plot. Outliers were deleted from the original data set.

The chemical composition of the produced water is influenced by a variety of effects. The water is directly affected by a wide selection of injected chemicals, e.g. from squeeze events, well clean-ups, re-stimulation and scale inhibitors. Back flow of these injected chemicals is expected to affect the chemical composition of the produced water. "Process water", typically occurring within the first few years of production, is especially affected (Schovsbo et al. 2017).

The samples with process water signatures are identified during the PCA analysis. Typically, they behave as outliers when compared to the rest of the samples. Once identified, the samples are normally characterised by unusually high concentrations of Ca^{2+} and K^{+}. Hence, the data analysis also functions as a data quality check.

We know from sampling protocols that chemicals are added to the produced water prior to analysis. One of the most common chemicals to add is acetic acid. This is amongst other reasons done to avoid bacterial growth. Obviously, this will affect the chemical composition of the analysed water. As a minimum, the Cl^{-} concentration is found to be larger than what was in the untreated sample.

Additionally, precipitation during transport and storage due to changed pressure and temperature conditions may come into play. Also, uncertainties in the performed analyses are present. Currently, we are investigating these effects and their impact by applying new measuring techniques and by launching new sampling protocols. The new results will be compared to the old to ensure data reliability.

5.2 Regional water types

Produced waters in the Danish North Sea exhibit a considerable compositional range with salinities from less than 85% to 330% compared to present day North Sea seawater salinity of 21 000 ppm (Table 1). The chalk formed in normal marine conditions and its initial pore water composition was likely comparable to present day values (Warren et al. 1994). The highly saline water present in fields above salt domes likely reflects original pore water being mixed with brines from the dome. The highest salinities thus reflect a higher degree of fluid communication by fracture flow and/or chemical diffusion within the field.

The presence of low salinity water, here defined as water with less than seawater Cl^{-} levels, suggests that some reservoirs were flushed in order to reduce the ionic strength from its original level. The fields with this component are present in the northern most part of the study area (Fig. 2). From here salinity increases towards south in the order (low to high) Valdemar/Roar-Tyra-Tyra SE-Halfdan (Fig. 3). This may suggest that the low salinity water originated North of Valdemar perhaps within the geological area called Tail End Graben known to be one of the kitchen areas for oil generation (Petersen et al. 2016). The low salinity water may reflect original fresh water within non-marine deposits or may be derived from water liberated during clay transformations (c.f. Osipov et al. 2003).

The two formation water end-member (FW2 and FW3, see Fig. 4) present in the Halfdan field occur in different parts of the field. The FW3 type is present on the southern flank of the field towards the Dan field and is clearly related to the presence of salt dome water (Schovsbo et al. 2017) whereas the low salinity type (FW2) appear to be local end-member in the compositional continuum that extends north to the Valdemar/Roar fields. Within the Halfdan field, this suggests that local gradients in compositions exist and that each well location will represent a mix of the formation water produced along the long horizontal well track in contrast to all wells having same discrete compositions. For modelling purposes, care thus has to be taken to establish the initial water composition at each well site instead of applying fixed compositions.

5.3 PLS-regression model of well performance

In order to illustrate the relationship between water chemistry and production performance in the Halfdan wells, we have used prediction of oil fraction in the production as a reference. We could also have used the prediction of oil production rate, which also would have provided valuable insights into the production drivers. The main difference between the two variables is, however, minor and therefore we have focussed on establishing the first principles in the relationships between water chemistry and oil fraction in the production stream.

In the PLS-regression models the number of days in production has been included in the X data. This parameter has a high impact on the predictability of the oil fraction, especially because the model with this parameter can compensate for temporal changes in the production. If the parameter "days in production" is not included in the PLS-regression then dedicated models for early versus later production will provide more optimal predictions.

5.4 Water types and oil production drivers

There is a marked difference and fundamentally different relationship between oil and gas production and water chemistry between the five Halfdan wells. Well A and B represent wells in the core part of the field characterised by high oil production rates and high oil fractions in the production stream. These well are characterised by efficient water flooding in which the oil fraction is inversely correlated to the appearance of injected seawater (Fig. 6B). In addition the correlation between production days with the oil fraction is less profound and has a low predictive value.

The produced formation water may originate from the oil zone itself; liberated "squeezed out" due to relative compaction as pressure is lowered; or is produced by frictional drag from within the oil stream. As pressure is reduced, water from deeper levels is also expected to flow due to compaction (Fig. 8). Well C also represent a central positioned well. However this well experienced severe water breakthrough of injected water early in its production history. This well can be modelled together with well A and B (Fig. 6A).

For Well D and E the oil fraction is strongly dependant on production days (Fig. 6F). Well E represents a well from a flank position of the field. In this well the produced water

(FW3) does not show any indications that injected seawater is produced as the oil fraction is lowered, instead, formation water is produced as the oil fraction is lowered (Fig. 8). The production of formation water will also lead to a pressure drop promoting some compaction of the chalk. Ca^{2+} has a positive correlation to the oil fraction (Fig. 6F). This may reflect water originating from both within the oil column and from the water leg.

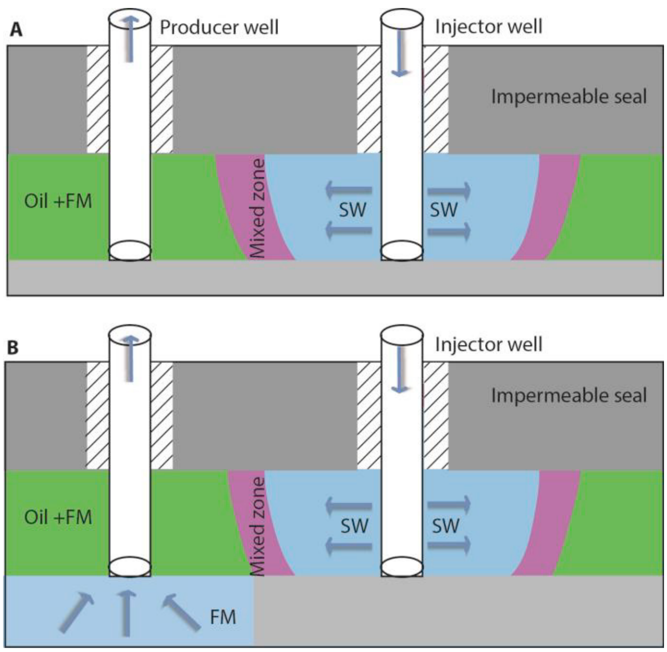

Fig. 8. Sketch of different water drive mechanisms A) Well A injection water drive and B) Well E combination of injection and compaction/aquifer water drive. Natural or induced fractures together with reservoir heterogeneities occur in all three scenarios. FW: Formation Water. SW: Sea Water.

6.0 PRODUCTION OPTIMISATION ON HALFDAN – BIG DATA

The key for success for the operation of the Halfdan field has been to link well data representing performance over many km and stimulation zones with seismic data that gives the spatial geometry (c.f. Calvert et al. 2014, 2016).

In order to obtain the full potential of the methods described in this paper, a successful implementation of water chemistry-oil production analytics should be transferred into other data domains such as seismic (4D) data and well work-over data.

Macroscopic sweep efficiencies are affected by a variety of variables (Table 2) including the geology, i.e. the inherited rock properties related to the depositional environments such as pelagic versus reworking, and the existence of natural or artificially created fracture network that will create short circuit fracture connections. These will overall lead to reduced recovery and possibly also to bypass of pay.

The data analytics may be the first step to a smart oil where digital oilfield workflows combine business process management with advanced information technology and engineering expertise to streamline and, in many cases, automate the execution of tasks performed by cross-functional teams.

Table 2. Factors influencing sweep and data sources

Key Factors Influencing Sweep Efficiency	Primary data type	Big Data Characteristics
Geology via porosity and permeability	Seismic data	Volume
	Well logs	Variety, Veracity
	Core data	Veracity, Sparse
	Stratigraphy	Variety, Veracity
Fractures creating short circuit connections	Production data	Volume, Velocity, Veracity
	Pressure data	Veracity, Sparse
Saturation and fluid mobility	Well logs	Variety, Veracity
	Production data	Volume, Velocity, Veracity
Micro sweep	Core data	Veracity, Sparse
	Fluid data	Veracity, Sparse
Well completion type	Unstructured text	Variety
Well completion: injecting / producing along the full length	Well production tests and logging	Veracity, Sparse
The Field master plan: Design of production and injection implementation	Integration of all relevant data available listed above for the given and analogue fields	Analytics, Data integration

Different business objectives in different departments, including a combination of disciplines involved in reservoir characterization, must be combined into common goals. Merging the static and dynamic features of a reservoir is the vital link between earth science and production engineering.

Monitoring fluid flow with 4D seismic techniques requires close collaboration between the disciplines of structural and stratigraphic geology, fluid flow simulation, rock physics, and seismology.

Analysis of various data sources should be used to continuously update and establish an accurate model of the reservoir system and from that obtain the ability to predict the consequences of implementing possible, alternative strategies. This can reduce the uncertainty associated with history matched models by verifying that the selected model is consistent with all the available data.

In other words we are dealing with a Big Data challenge, where we need to combine various data sources characterized by different levels of Volume, Velocity, Veracity, and Varieties in order to create Value. This should be achieved by analysing these data, updating the reservoir model, making predictions and recommendations, and finally implementing the recommendations, subject to management approval.

7. CONCLUSIONS

The present study confirms that multiple parameters control production. Produced water chemistry data can be used advantageously in direct PLS prediction to determine key production drivers.

The database can be extended to include more of the comprehensive data available from the fields. Based on an augmented data set, it is in principle a simple task to refine this pilot study to investigate the more general limits of the feasibility demonstrated.

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